Nonlinear Loan Loss Provisioning

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Abstract

The extant banking literature often models loan loss provisions as a linear function of changes in loan portfolio quality. Large sample data indicate that this linearity assumption is invalid and that a V-shaped piecewise linear specification fits much better. Decreases in nonperforming loans are associated with *increases* in loan loss provisions. This anomalous asymmetric relation is partly driven by the mechanical accounting effects of loan charge-offs on nonperforming loans and allowance for loan losses. We find that, controlling for concurrent loan charge-offs, loan loss provisions move in the same direction as nonperforming loan change, but asymmetry remains. The effect of nonperforming loan increases on loan loss provisions is still twice as large as that of nonperforming loan decreases. We argue that the residual asymmetry is caused by conditional conservatism. We show that loan loss provision asymmetry is greater for banks with more high-risk construction loans, shorter-maturity loans and for public banks, and is more pronounced during economic downturns and in the fourth quarter, consistent with the predictable effects of conditional conservatism.

Keywords: loan collectibility, loan duration, conditional conservatism

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1. Introduction

Banks seek to reserve or allow adequately for expected losses when reporting the net realizable values of their loan portfolios. End-of-period adjustments to the allowance for loan losses are charged through loan loss provisions, which combine historical credit loss experience, statistical analysis and subjective judgment. Since loan loss provisions are a large expense for banks (averaging one tenth of net interest income), many researchers study banks' "abnormal" or "discretionary" loan loss provisions. The standard approach (cf. Beatty and Liao 2014) models the "normal" loan loss provision as a linear function of observable credit risk indicators (e.g., change in nonperforming loans), implicitly assuming that loan loss provisions vary proportionally with changes in problem assets absent earnings manipulation.

We evaluate this linearity assumption and find that loan loss provisions have a V-shaped relation with changes in nonperforming loans. Figure 1 presents a binned scatter plot of quarterly loan loss provisions against quarterly changes in nonperforming loans for all bank holding companies during 2000Q1-2015Q4. We divide the horizontal axis into 20 equal-frequency (quantile) bins and plot mean loan loss provisions against mean change in nonperforming loans (both deflated by beginning loans) in each bin. The relation between loan loss provisions and change in nonperforming loans is unmistakably nonlinear, as compared to the red-dashed OLS line, whose misspecification causes wide 95% confidence intervals. Consistent with the assumed linearity, loan loss provisions increase almost proportionately to increases in nonperforming loans. However, the positive slope flattens as nonperforming loans decrease, and in the left tail of the distribution with large nonperforming loan decreases, the relation slopes *down* instead of up. Importantly, the wide 95% confidence interval for the OLS line does not overlap with much of the data, especially at the tails and in the middle of the distribution, which could easily lead to incorrect inferences.

We propose a piecewise linear model to more accurately summarize the joint distribution of loan loss provision and nonperforming loan changes. We first compare our piecewise linear models with the standard linear models reviewed in Beatty and Liao (2014). Many recent studies do not control for current-period loan charge-offs (realized loan losses) when modelling loan loss provisions. Loan charge-offs are innately related to loan loss provisions, reducing both nonperforming loans and allowance for loan losses on the balance sheet one-for-one. We argue that sufficiently large loan charge-offs can cause reported nonperforming loans to decrease despite an increase in other problem loans, and to restore an appropriate allowance, management must increase provisions, causing the downward sloping portion of Figure 1. Once we include loan charge-off as an explanatory variable, loan loss provisions decrease when nonperforming loans decrease, which is more in line with existing accounting/regulatory guidance and industry practice.

However, some asymmetry remains. After controlling for the effect of loan charge-offs, a \$1 increase in current-period nonperforming loan increases provisions by 7.3 cents, whereas a \$1 decrease in current-period nonperforming loans decreases provisions by only 3.9 cents. We explore conditional conservatism as an explanation for the remaining loan loss provision accrual asymmetry, since conservatism causes accrual asymmetry (e.g. Basu 1997; Ball and Shivakumar 2005, 2006) and banks report in a conditionally conservative manner (e.g. Nichols, Wahlen and Wieland 2009; Black, Chen, and Cussatt 2018). To the extent that increases (decreases) in nonperforming loans reflect unrealized credit losses (gains) in the loan portfolios, conditional conservatism implies a higher verification threshold for recognizing nonperforming loan increases than nonperforming loan decreases.

We show next that the residual loan loss provision asymmetry varies predictably with some theoretical sources of conditional conservatism (e.g., Basu 1997; Watts 2003a). First, we find that the residual asymmetry increases with concurrent loan charge-offs. Increases in nonperforming loans coupled with significant charge-offs serve as a more credible indicator of probable credit losses, which should amplify the asymmetric timeliness of loan loss provisioning (Banker et al. 2017). Second, we find that the asymmetry is sharpest when banks have a larger share of construction loans. Loans that finance construction projects are risky because the project is incomplete and generates no cash flows and are evaluated individually. Contrarily, for banks concentrated in residential real estate and consumer loans that are evaluated as homogenous pools, where unrealized losses on some loans are offset by unrealized gains on others, we find predictably less loan loss provision asymmetry.

Next, we show that banks with larger shares of short-maturity loans exhibit greater asymmetry in loan loss provisions, consistent with nonperforming loan change serving as a short-term predictor for future cash flows in loan impairment decisions. The asymmetry is greater during economic recessions when borrowers' repayment ability worsens and the fair value of the underlying collateral is depressed. Finally, we find that the asymmetry is strongest in the fourth quarter and for public banks, reflecting supply of conditional conservatism by auditors and demand from the stock market.

We conclude the paper by evaluating the power and specification of the competing models for earnings management tests. Our simulation analysis shows that absent controls for concurrent charge-offs, linear models of nondiscretionary loan loss provisions reject excessively in favor of upward (downward) earnings management in subsamples with extreme (moderate) nonperforming loan change, and they lack power for earnings management of plausible magnitude in the full sample. We show that researchers can substantially reduce misspecification by incorporating piecewise linearity and (or) concurrent charge-offs, and that including loan charge-offs alone increases model power considerably.

We contribute by showing that the conventional linear model of loan loss provisions is misspecified by not incorporating two sources of asymmetry. We extend prior research on the "normal" process of accruals (e.g. Dechow 1994; Dechow and Dichev 2002; Nikolaev 2018), accounting conservatism (e.g., Basu, 1997; Ball and Shivakumar 2006; Byzalov and Basu 2016), and the timeliness of loan loss provisions (e.g., Nichols et al. 2009; Beatty and Liao 2011; Lim et al. 2014; Akins, Dou, and Ng 2017; Nicoletti 2018). Our findings suggest that, at a minimum, researchers should use loan charge-offs to predict loan loss provisions, which removes most, but not all, of the nonlinearity biases.

2. Institutional Background and Hypothesis Development

2.1. Institutional Background

Both U.S. GAAP and regulatory guidance institutionalize longstanding reporting practices for bank loan portfolios. Under U.S. GAAP, loans are impaired under an "incurred loan loss model," where allowances are provided for losses that are incurred, probable and reasonably estimable based on management's existing information about the loan portfolio.[1] The allowance for loan losses is a contra-asset account, reducing the net carrying value of the loan to estimated net realizable value. Period-end adjustments to the allowance for loan losses are made through a loan loss provision, which is similar to bad debt expense and reduces banks' net income. Banks charge off loans, or portions thereof, when losses are later realized on an ongoing basis, by

[1] In June 2016, the Financial Accounting Standards Board (FASB) issued Accounting Standards Update (ASU) 2016-13, Financial Instruments - Credit Losses (Topic 326): Measurement of Credit Losses on Financial Instruments, which replaces the existing incurred loss impairment methodology with a current expected credit loss methodology (also known as "CECL"). Banks will be required to recognized expected credits losses "over the contractual term of the financial asset(s)", considering available information about the collectability of cash flows, including information about "past events, current conditions, and reasonable and supportable forecasts." (see ASC 326-20-30). CECL will be effective in 2020 for SEC registrant banks and 2021 for all other banks.

reducing the allowance and loan balances one-for-one, while leaving net income unaffected. Loan loss provisioning is guided by two related standards depending on whether the loans are individually identified for impairment: 1) loans identified for evaluation or that are individually considered impaired are accounted for under the Receivables Topic of Accounting Standards Codification ("ASC") 310 (formerly SFAS 114, FASB 1993), and 2) non-impaired loans are provided general valuation allowances in accordance with the Contingency Topic of ASC 450 (formerly SFAS 5, FASB 1975).

Banks individually evaluate certain impaired loans—typically larger-balance business loans including commercial and industrial (C&I) loans and commercial real estate (CRE) loans—and establish specific allowances for such loans if required, under ASC 310-10-35, *Receivables - Subsequent Measurement*. A loan is impaired when, based on available information, it is probable that a creditor will be unable to collect *all* contractually due interest and principal payments. Under this definition, loans for which interest no longer accrues (nonaccrual loans) are considered impaired, and the related allowances for loan losses are determined individually. Impairment is measured by comparing the present value of expected future cash flows, discounted at the loan's historical effective interest rate, to the recorded investment of the loan. The allowance is sometimes determined using the loan's fair value or the fair value of collateral for collateral-dependent loans. Any subsequent change in impairment is reported as an adjustment to the allowance for loan losses through a loan loss provision. Per ASC 310-10-35-21, banks must set aside a specific valuation allowance for individually impaired loans that have risk characteristics unique to borrowers. Banks may aggregate individually impaired loans that share common risk characteristics and provide a general valuation allowance based on quantitative historical loss data of the loan group. Hence, the allowance for impaired loans usually contains both a specific and a general reserve component.

Loans that do not meet the criteria to be individually evaluated are grouped into homogeneous pools of loans with similar risk characteristics and collectively evaluated for impairment, in accordance with ASC 450-20 *Contingencies - Loss Contingencies.* Losses inherent to each loan pool are statistically calculated using estimated probability of default and loss given default for the pool, derived from many risk factors including, but not limited to, changes in current economic condition, historical loss experience, and trends with respect to delinquent loans. Management adjusts the quantitative loss estimates using qualitative judgments, correcting for imprecision in the estimation models, to ensure an adequate overall allowance. A general valuation allowance is then determined for each loan pool. When assets are grouped into pools of similar characteristics for impairment, impairment triggers can be "loose," reducing the frequency and amounts of impairment (Basu 2005; Byzalov and Basu 2016). This arises because unrealized losses on some assets can be offset by unrealized gains on other assets in the same pool. The prediction is that homogenous loans that are collectively evaluated for impairment will be less asymmetrically timely than individually impaired loans with respect to nonperforming loan change.

2.2. Hypothesis Development

We focus on the sensitivity of loan loss provisions to changes in nonperforming loans for three reasons. First, nonperforming loans are a relatively nondiscretionary credit quality indicator (Liu and Ryan 2006), which fits our objective of modelling the "normal" process of loan loss accruals absent earnings manipulation. Second, nonperforming loans reflect receivables' payment delinquency status, which is a key trigger of probable defaults and impairments under FASB's incurred loan loss approach. Third, the extant loan loss provision models assume a linear relation with nonperforming loan change.

To properly characterize the relation between loan loss provisions and nonperforming loan change, we propose that researchers, at a minimum, should control for the mechanical accounting effects of concurrent loan charge-offs (realized credit losses), which reduce both nonperforming loans and allowance for loan losses on the balance sheet one-for-one. When loan charge-offs are sufficiently large in a period, reported nonperforming loans can decrease, instead of increase, despite the underlying adverse trends in the credit portfolio. To replenish the allowance for loan losses, managers must increase provisions, and bigger decreases in nonperforming loans induce *larger* loan loss provisions. We show that imposing a linear specification without including loan charge-offs results in severe omitted variable bias, leading to the puzzling V-shaped relation between loan loss provisions and nonperforming loan changes in Figure 1.

We argue that after controlling for concurrent loan charge-offs, loan loss provisions should decrease when nonperforming loans decrease. However, we expect bank loan loss provisions to be more sensitive to nonperforming loan increases (unrealized credit losses) than to nonperforming loan decreases (unrealized credit gains) reflecting conditional conservatism.

While condition conservatism is pervasive (e.g., see reviews by Watts 2003b, Ryan 2006 and Barker and McGeachin 2015), and by definition flows through accruals (e.g., Basu 1997; Ball and Shivakumar 2005, 2006; Hsu, O'Hanlon and Peasnell 2011, 2012; Collins, Hribar and Tian 2014; Byzalov and Basu 2016; Larson, Sloan and Giedt 2018), the existing loan loss provision (accrual) literature largely ignores the potential impact of conditional conservatism. An exception is Nichols et al. (2009), who find that the slope coefficient for nonperforming loan change is larger for public banks than for private banks, and interpret this finding as public banks having timelier loan loss provisioning than private banks. However, their model does not differentiate between nonperforming loan decreases and increases, and therefore cannot speak to the conditional conservatism of loan loss provision. [2]

We posit that regulatory oversight on allowance adequacy, existing accounting guidance for loan loss provisions, and management's judgment in evaluating loan impairments are all likely to contribute to conditional conservatism in loan loss provisioning. Bank regulators, as an integral part of their supervisory functions, periodically review banks' loan portfolios and the adequacy of the allowance for loan losses. The Commercial Bank Examination Manual states that "the examiner's responsibility to determine the adequacy of a bank's ALLL (Allowance for Loan and Lease Losses) is one of the most important functions of any examinations" (Federal Reserve Board of Governors, 1999). By monitoring loan loss reserve adequacy, regulators aim to mitigate adverse impacts of allowance shortfalls on bank stability and consumers' (e.g., depositors and borrowers) welfare. According to the Interagency Policy Statement on the Allowance for Loan Losses, "prudent, conservative, but not excessive, loan loss allowances that fall within an acceptable range of estimated losses are appropriate." Of course, banks discovered that prudent loan loss reserves helped survival centuries before bank regulators and accounting standard-setters were created.

Changes in nonperforming loans represent likely credit gains and losses. Prior conservatism research reports that recognition of unrealized gains and losses is asymmetric in earnings and accruals (Basu 1997; Ball and Shivkumar 2006; Beaver and Ryan 2005). Larson et al (2018) systematically evaluate accruals and observe that a major role of accruals (besides

[2] While recent papers study the timeliness of loan loss recognition, they do not differentiate between the effects of nonperforming loan increases and decreases. For example, Akins et al. (2017) measure timeliness of loan loss recognition as the ratio of allowance for loan loss reserves at time t to nonperforming loans at time t+1. Because this measure does not account for the asymmetric effects of nonperforming loan change, it likely captures the kind of banks with unconditionally large (or even excessive) allowances relative to nonperforming loans. Andries, Gallemore, and Jacob (2017) find that loan loss provisions are timelier in countries that permit tax deductibility for loan loss provisions. Although not key to their argument, their models do not speak to conditional conservatism in loan loss provisioning, since they assume a constant slope coefficient. Neither paper accounts for the mechanical effects of loan charge-offs, which we show is an important source of loan loss provision asymmetry.

alleviating transitory cash flow effects and capturing investments related to firm growth) is to reflect conditional conservatism, where assets must be written down or impaired if their fair values drop sufficiently below their carrying values. Because market prices for loans held for investment are often not readily available, the "fair value" of a loan is usually an entity-specific (rather than market-based) metric defined as the present value of expected future interest and principal payments discounted at the loan's effective interest rate, which is compared to the bank's recorded investment in the loan.[3] If a loan's quality deteriorates enough to be classified as "nonperforming", expected future cash flows from the loan likely have dropped sufficiently below the contracted principal and interest amounts, which would trigger loan loss accruals. Since conditional conservatism is a key property of accrual accounting, we predict that loan loss provisions will correspond more strongly to nonperforming loan increases (unrealized losses) than to nonperforming loan decreases (unrealized gains).

The asymmetry in the recognition of unrealized credit losses and gains is consistent with losses being accrued when probable and estimable under ASC 450-20, *Contingencies - Gain contingencies,* while gain contingencies are usually not recorded until realized under ASC 450-30, *Contingencies - Gain contingencies*. Institutional evidence suggests that bank managers use conservative judgment in reducing loan loss reserves when borrower repayment performance improves. For example, M&T Bank Corporation (2017 Form 10-K, Item 6) said, "Considering the inherent imprecision in the many estimates used in the determination of the allocated portion of

[3] Recorded investment is the amount of the investment in a loan, which, unlike carrying value, is not net of valuation allowance, but which does reflect any direct write-downs of the investment (ASC 310-10-35). For collateral dependent loans, loan impairment is measured as the excess of the recorded investment in the loan over the fair value of the underlying collateral per ASC 320-10-35.

the allowance, management deliberately remained cautious and conservative in establishing the overall allowance for credit losses." [4]

While the relation between loan loss provisions and change in nonperforming loans is unlikely to change slope at exactly a nonperforming loan change of zero (e.g. Basu, 2005), we predict loan loss provisioning to be more responsive to deterioration in portfolio credit quality than to improvements in portfolio credit quality, which leads to the following hypothesis:

***H1*: **Loan loss provisioning is piecewise linear with respect to increases versus decreases in nonperforming loans, after controlling for concurrent loan charge-offs.

3. Data

3.1. Sample

We use data from the Federal Reserve (FR) Y-9C Reports, which provide detailed quarterly income statement and balance sheet data for all U.S. commercial bank holding companies. Appendix A defines all the variables we study. Our primary sample is an unbalanced panel of 79,070 bank-quarter observations from 2,760 bank holding companies during 2000Q1 to 2015Q4. We log bank size to reduce right skewness and winsorize all other continuous variables at the top and bottom 1% to mitigate the influence of outliers. Our results are robust to using Compustat Bank data as an alternative source of financial data for publicly listed banks.

3.2. Summary Statistics

Table 1 Panel A reports descriptive statistics for our main regression variables. Quarterly loan loss provision scaled by beginning-of-period loan balance (*LLP*) has a mean of 0.14% with a

[4] M&T Bank (Form 10-K, Item 6) also states, "Management *cautiously* and *conservatively* evaluated the allowance for credit losses as of December 31, 2017…. While there has been general improvement in economic conditions, concerns continue to exist about the strength and sustainability of such improvements." The 10-K can be accessed via https://www.sec.gov/Archives/edgar/data/36270/000156459018002855/mtb-10k_20171231.html.

standard deviation of 0.26%.[5] As in prior research (e.g., Bushman and Williams 2012, 2015), we include lead, current and two lagged changes in nonperforming loans (ΔNPL_{t+1}, ΔNPL_t, ΔNPL_{t-1}, ΔNPL_{t-2}) in our regressions. Nonperforming loans are defined as 1) loans past due 90 days or more and no longer accruing interest plus 2) loans past due 90 days or more and still accruing interest, scaled by beginning loans. ΔNPL_t averages 0.03% with a standard deviation of 0.57%. Net loan charge-offs (*NCO*), defined as gross loan charge-offs minus recoveries averages 0.12% of beginning-of-period loans with a standard deviation of 0.23%. On average, allowance for loan losses (*ALL*) comprises 1.52% of total loans. Bank asset size (*SIZE*), defined as the logarithm of total assets, averages 13.65 with a standard deviation of 1.39. Banks' quarterly loan growth rate ($\Delta LOAN$) averages 2.01%.

Panel B reports Pearson (Spearman) correlations between the variables below (above) the diagonal. Large differences in these correlation coefficients for the same variable pairs suggest strong nonlinearity (e.g. *LLP* paired with ΔNPL_t, *NCO* or *ALL*). *LLP* correlates positively with ΔNPL across all four time periods. *NCO* and *LLP* are highly positively correlated, consistent with the mechanical accounting relation between them.

Figure 2 presents a binned scatter plot of *LLP* versus *NCO*. We group *NCO* into 20 equal-frequency bins (quantiles) and plot the mean *NCO* versus mean *LLP* by quantile bin. In contrast to the V-shaped curve in Figure 1, the relationship between *LLP* and *NCO* is almost perfectly linear, with a covariance close to one (i.e., the trend line is 45 degrees).

4. Piecewise Linear Specification

4.1. *Model*

Our main regression employs the following piecewise linear specification:

[5] In untabulated analyses, quarterly loan loss provisions average 11.5% of quarterly net interest income, suggesting that loan loss provisions have a nontrivial negative impact on bank profitability.

$$LLP_{it} = \sum_{j=-1}^{2} \Delta NPL_{it-j}\,(\alpha_j + \beta_j D\Delta NPL_{it-j}) + \sum_{J=-1}^{2} \theta_j D\Delta NPL_{it-j} + \chi'_{\mathrm{it}} + \lambda_i + \sigma_t + \epsilon_{it} \qquad (1)$$

where *i* indexes bank and *t* indexes year-quarter. ΔNPL_{it} represents the change in nonperforming loans from quarter *t-1* to quarter *t* scaled by quarter *t-1* total loan balance. *j* can assume values (-1, 2) to incorporate lead, concurrent, and two lagged changes in nonperforming loans. ΔNPL_{t-1} and ΔNPL_{t-2} are included because banks consider historical trends in loan delinquency in accruing loan loss reserves. ΔNPL_{t+1} captures how well loan loss provisions predict next-period loan delinquency. We predict the coefficients on ΔNPL_{t}, ΔNPL_{t-1}, and ΔNPL_{t-2} to be positive; i.e., loan loss provisions positively correlate with both current and lagged nonperforming loan changes. Under current GAAP's incurred loss model, allowance for loan losses is established to reflect probable credit losses that have already been incurred (ASC 310; ASC 450), and as such current-period provisions for loan losses should have limited predictive power for future loan delinquencies. On the other hand, bank regulators impose a relatively more forward-looking approach in evaluating the adequacy of valuation allowances, with an emphasis on whether banks can cushion against future adverse credit and economic conditions (Beatty and Liao 2011; Nicoletti 2018). As such, the point estimate for ΔNPL_{t+1} is predicted to be weakly positive or insignificant.

$D\Delta NPL_{t-j}$ are binary indicators that equal one for $\Delta NPL_{t-j} < 0$, and zero otherwise. While we do not have a prediction for the α_j intercept coefficients on these variables, H1 predicts that the incremental slope β_j coefficients for decreases relative to increases in nonperforming loans (the coefficient on $D\Delta NPL_{t-j} \times \Delta NPL_{t-j}$) are negative. In addition, when controlling for loan charge-offs, H1 predicts that the slope coefficient for current nonperforming loan decreases (the summed coefficient on ΔNPL_{t} and $D\Delta NPL_{t} \times \Delta NPL_{t}$) is positive, that is, loan loss provisions decrease when current nonperforming loans decrease.

The vector of time-varying bank-specific control variables, χ'_{it}, includes $SIZE_{t-1}$, $\Delta LOAN_t$, NCO_t, and ALL_{t-1}. The first two variables are included in all four models reviewed by Beatty and Liao (2014) and studies cited therein, whereas the latter two variables are included in some, but not all, models. As already seen in Figure 2 above, we expect the coefficient on NCO_t to be close to one because of "mechanical" accounting effects. ALL_{t-1} is included to capture the impact of cumulative prior loan loss accruals on current period loan loss provisions.[6] λ_i and σ_t represent bank fixed effects and year-quarter fixed effects, respectively. To account for correlations in the error term ϵ_{it} across banks and over time, we double cluster standard errors at the bank and year-quarter level. We report adjusted R^2, within-bank adjusted R^2, Akaike information criterion (AIC) and Bayesian information criterion (BIC) to evaluate model fit.

4.2. Baseline Results

Table 2 reports the baseline results. We first estimate several linear specifications and report the results in Panel A. Column (1) replicates the linear model that, based on Beatty and Liao's (2014) review, best detects serious loan loss provision management as reflected by accounting restatements and SEC comment letter receipts (Model (a) in their Table 4). This model is commonly used (e.g., Bushman and Williams 2012; Jiang et al. 2016; Nicoletti 2018). The model includes several quarterly macroeconomic variables: GDP change (ΔGDP_t), the return on the Case-Shiller Real Estate index (ΔCS_t), and the change in unemployment rate ($\Delta UNEMPLOY_t$). Column (2) replaces the quarterly macroeconomic variables in column (1) with year-quarter fixed effects, and column (3) additionally controls for bank fixed effects. Column (4) includes ALL_{t-1}, which is similar to Model (c) in Beatty and Liao (2014), with time fixed effects in place of their

[6] On the one hand, ALL_{t-1} can be positively related to LLP_t to the extent that past cumulative loan losses are an indication of current period loan losses. On the other hand, the relation can be negative since, all else equal, bank management accrues fewer provisions if the existing allowance is adequate (Bhat, Ryan, and Vyas 2018).

macroeconomic variables. The last column also controls for NCO_t, which resembles model (d) in Beatty and Liao (2014).

All five models find a strong, positive relation between loan loss provisions and current-period change in nonperforming loans. The slope coefficient for ΔNPL_t ranges from 0.042 in column (3) to 0.057 in column (5). The next-period and the past-two-periods' ΔNPL are also positively associated with LLP. Adjusted R^2 improves monotonically from columns (1) through (5), with column (5) having by far the largest incremental adjusted R^2 and within-bank adjusted R^2 due to inclusion of NCO_t. In column (5), the slope coefficient for NCO_t is 0.792 and highly significant, suggesting that a $1 increase in NCO_t is associated with a 79 cent increase in LLP_t.[7]

In Panel B we present estimates of the piecewise linear specifications outlined in equation (1). Consistent with Figure 1, absent controls for NCO_t, loan loss provisions exhibit severe asymmetry with respect to increases versus decreases in NPL. Columns (1)–(4) show that while the slope coefficient for increase in NPL_t is significantly positive, the slope coefficient for decrease in NPL_t is significantly negative (summed coefficient on ΔNPL_t and $D\Delta NPL_t \times \Delta NPL_t$). The estimates in column (4), for instance, indicate that while a $1 increase in NPL_t corresponds to a 11.5 cent increase in LLP_t on average, a $1 decrease in NPL_t corresponds to a 4.9 cent *increase* (=0.164 - 0.115) in LLP_t on average. Moving from columns (1) to (4), adjusted R^2 improves by 11.5, 10.7, 6.4 and 2.7 percentage points compared to their linear versions in Panel A. For columns (3) and (4) that include bank fixed effects, within-bank adjusted R^2 also improves by 4.9 and 3.6 percentage points, suggesting that modeling asymmetry helps better explain both overall and within-bank variation in loan loss provisions. Both the AIC and BIC statistics also indicate that

[7] The slope coefficient of 0.792 for *NCO* is very similar to the coefficient estimate of 0.788 in Beatty and Liao's (2014) model (d) in Table 4.

the piecewise linear specifications provide a better fit, relative to the corresponding linear specifications in Panel A.

Column (5) presents estimates of incorporating NCO_t as an explanatory variable. We find that controlling for NCO_t substantially reduces, but does not eliminate, *LLP* asymmetry. The coefficient on $D\Delta NPL_t \times \Delta NPL_t$ in column (5) is smaller than those in the first four columns but remains large and statistically significant at the 1% level. After controlling for NCO_t, loan loss provisions decrease as *NPL* decrease. A $1 increase (decrease) in NPL_t increases (decreases) LLP_t by 7.3 cents (3.9 cents). Figure 3 Panel A plots the relation between the portion of loan loss provisions unexplained by loan charge-offs which is the residual from a regression of LLP_t on NCO_t. After removing the effects of NCO_t, loan loss provisions generally move in the same direction as ΔNPL (the V-shaped nonlinearity disappears), although the slope is steeper for *NPL* increases than for *NPL* decreases.

In column (6), we address the mechanical accounting effects of *NCO* differently. Instead of including NCO_t as a standalone explanatory variable, we add NCO_t to ΔNPL_t to create a modified credit loss indicator ($\Delta NPLNCO_t$).[8] One limitation of combining ΔNPL_t and NCO_t is that it forces them to have the same slope coefficient, which is clearly wrong given our evidence thus far. The point estimate for $D\Delta NPLNCO_t \times \Delta NPLNCO_t$ is negative and significant (coefficient = -0.153; *t*-statistic = -23.16). The summed coefficient on $D\Delta NPLNCO_t$ and $D\Delta NPLNCO_t \times \Delta NPLNCO_t$ is 0.002 (= 0.155 - 0.153), which indicates that the slope coefficient for decreases in $NPLNCO_t$ is

[8] To illustrate the intuition behind this approach, suppose a bank has a $100 decrease in nonperforming loans, and, for simplicity, assume that half of the decrease ($50) is due to charge-offs and the other half due to genuine credit quality improvement. The modified measure of nonperforming loan change will equal -50 (= -100 + 50), reflecting the $50 improvement in loan portfolio quality and avoiding misinterpretation related to charge-offs. Alternatively, suppose that the underlying credit quality deteriorates, and the bank experiences a $50 increase in nonperforming loans while charging off $50 loans for a net change of zero. The modified loan loss indicator equals $100 (= 50 + 50), which captures jointly the rising delinquency and confirmed credit losses (charge-offs) due to credit quality deterioration.

almost flat. Model fit diagnostics indicate that this alternative specification does not fit as well as the specification that directly controls for NCO_t (column [5]). Figure 3 Panel B presents a binned scatter plot of LLP_t versus $NPLNCO_t$. Compared to Figure 1, adding NCO_t to ΔNPL_t reduces, but does not eliminate, the V-shape pattern. [9]

The combined evidence suggests that omitting loan charge-offs contributes most of the asymmetric effects of nonperforming loan change. As predicted in H1, even after controlling for loan charge-offs, the effect of nonperforming loan increases is twice as large as that of nonperforming loan decreases. Thus, the residual asymmetry is likely explained by sources other than loan charge-offs.[10]

We test the robustness of our findings by including additional control variables. In untabulated tests, we obtain similar estimates when we augment equation (1) with earnings before loan loss provisions, Tier1 risk-based capital ratios, loan portfolio composition variables (including the ratios of construction loans to total loans, the ratio of commercial loans to total loans, and the ratio of residential real estate loans to total loan), as well as the past-two-period loan charge-offs as explanatory variables. We emphasize that including only historical loan charge-offs, but not concurrent loan charge-offs, still results in V-shaped nonlinearity where the slope for current nonperforming loan decreases is negative. Thus, to remove the "mechanical" effect of loan

[9] We perform an untabulated semi-parametric analysis that does not impose a specific functional form. We divide ΔNPL into 20 equal-frequency (quantile) bins and assign an indicator for each bin. We regress *LLP* on the bin indicators, bank controls, bank fixed effects and year-quarter fixed effects. Absent control for *NCO*, the coefficient estimates for ΔNPL quantile dummies exhibit a U-shaped pattern. Specifically, the relation between *LLP* and ΔNPL is negative below the 25th percentile of ΔNPL, nearly flat between the 25th and the 50th percentile, and positive beyond the 50th percentile. Controlling for *NCO* removes this U-shaped pattern. The coefficient estimates for the ΔNPL bin indicators on *LLP* now increase almost monotonically, with the positive slope being much steeper in the top 15th percentile of ΔNPL.

[10] We obtain similar estimates using annual bank data. After controlling for *NCO*, a $1 increase in nonperforming loans is associated with 12.8 cent increase in *LLP*, whereas a $1 decrease in nonperforming loans is associated with 7.4 cent decrease in *LLP*

charge-offs on current-period loan loss provisions and reduce the significant nonlinearity bias, researchers should always include concurrent loan charge-offs, not lagged loan charge-offs.

5. Conditional conservatism and asymmetric nonlinearity in loan loss provisioning

We next explore whether the residual loan loss provision asymmetry (after removing the charge-off effects) varies predictably with the theoretical sources of conditional conservatism (Basu 1997; Watts 2003a). Although prior research shows that conditional conservatism pervades the normal accrual process, the existing loan loss provision literature does not account for the impact of conditional conservatism. Just as the broader accruals management literature is unreliable because it does not model conditional conservatism (Ball and Shivakumar 2006; Byzalov and Basu 2016), we suspect that the loan loss provision (a large banking accrual) models can be improved by incorporating conditional conservatism.

5.1 The incremental effect of loan charge-offs

We first evaluate whether *NCO* has an incremental impact on asymmetry. If increases in nonperforming loans are accompanied by large charge-offs, then we expect management to have a more precise indicator of loan portfolio deterioration and to more quickly incorporate nonperforming loan increases in calculating allowance for loan losses. Both ΔNPL and *NCO*, to varying degrees, reflect loan portfolio quality. When the two indicators are consistent with each other, the credit loss factor contained in ΔNPL is likely more credible, which according to Banker et al. (2017), makes *LLP* more sensitive to bad news (nonperforming loan increases).[11]

[11] In addition, because loan charge-offs mechanically decrease nonperforming loans one-for-one, the fact that nonperforming loans increase despite the offsetting effects of loan charge-offs is a strong indication of deterioration in the bank’s loan portfolios. Thus, bank management is likely to be more conservative in establishing valuation allowances for nonperforming loans in response to large loan charge-offs.

Figure 4 illustrates the interaction effects of charge-offs on the asymmetric timeliness of loan loss provisions. We sort our sample into quartiles based on *NCO*, and within each *NCO* quartile we further sort the observations into 20 equal-frequency (quantile) bins by *ΔNPL*. We plot mean *LLP* against mean *ΔNPL* for each bin within each *NCO* quartile. All four curves exhibit V-shaped relations between *LLP* and *ΔNPL*. As predicted, the V-shape appears to be sharpest in the top *NCO* quartile.

We formally test the interaction effect of charge-offs by estimating the following regression:

$$\begin{aligned} LLP_{it} = \beta_0 &+ \beta_1 D\Delta NPL_{it} + \beta_2 \Delta NPL_{it} + \beta_3 D\Delta NPL_{it} \times \Delta NPL_{it} + \beta_4 D\Delta NPL_{it} \times NCO_{it} \\ &+ \beta_5 \Delta NPL_{it} \times NCO_{it} + \beta_6 D\Delta NPL_{it} \times \Delta NPL_{it} \times NCO_{it} \\ &+ \beta_7 NCO_{it} + \chi'_{it} + \lambda_i + \sigma_t + \epsilon_{it} \end{aligned} \tag{2}$$

Where the coefficient of interest is β_6 on the interaction *DΔNPL×ΔNPL×NCO*, which we predict to be negative. We include all the control variables including *NCO*, bank fixed effects and year-quarter fixed effects as in equation (1). For parsimony, we focus on the *contemporaneous ΔNPL–LLP* relation because conditional conservatism flows through accruals based mainly on available information reflecting *current* change in credit condition. Our results are robust if we incorporate both lead and two lags of *ΔNPL*, asymmetries, and their interactions with *NCO*.

Table 3 reports the regression estimates. The coefficient on *ΔNPL* × *NCO* is positive and significant, suggesting that the positive slope of *LLP* for *NPL* increases is steeper when *NCO* is greater. A one standard deviation (0.23 percentage point) increase in *NCO* is associated with a 16% (0.0023 × 3.728 / 0.054) increase in the positive slope of *LLP* for *NPL* increases. *LLP* asymmetry is greatest in periods of larger charge-offs. The point estimates imply that when *NCO* increases by one standard deviation, asymmetry increases by 38.5% (0.0023 × 4.688 / 0.028).

Thus, the evidence supports our prediction that asymmetry increases with current charge-offs, which is our first piece of evidence that conditional conservatism also causes *LLP* asymmetry.

5.2. The incremental effect of loan portfolio composition

We next test whether asymmetric timeliness is greater when impairment is tested on individual assets rather than on asset pools (Basu 2005 and Byzalov and Basu 2016). When assets are aggregated into pools of similar assets for impairment testing, unrealized losses in some assets could be offset by unrealized gains in other assets, thus decreasing, on average, the frequency and amount of impairment recognized for the pool. Byzalov and Basu (2016), for example, find that modelling accruals using segment-level indicators for unrealized future cash flows adds incremental explanatory power over firm-level indicators.

Loan allowance methodology varies by loan type. Residential mortgages and non-mortgage consumer loans such as credit card loans are typically segmented into homogeneous pools of similar risk characteristics to assess valuation allowances. Banks do not individually test impairments for such loans and rely mostly on formula-based statistical analysis to estimate allowances, which is more likely to induce a proportional relation between loan loss provisions and change in nonperforming loans (Liu and Ryan 1995). On the other hand, commercial loans are more idiosyncratic, and once repayment falls behind, banks need to individually evaluate those loans (especially larger-balance ones) for impairment. In calculating impairment for specific loans, management considers a wide range of quantitative and qualitative factors and are likely to take a more conservative judgment about borrowers' abilities to repay. Among commercial loans, construction loans are particularly risky due to lack of supporting cash flows as collateral and the uncertain nature of construction projects. We thus expect banks to be more be more conditionally conservative if construction loans comprise a larger share of the banks' loan portfolio.

We separate loans into four types: construction loans, commercial loans (commercial real estate loans plus commercial and industrial loans), residential real estate loans, and consumer loans (e.g., credit card loans). We study how loan loss provision asymmetry varies with banks' loan portfolio concentration in each of the four loan types. We divide the amount of each of the loan types by total loan balance and code decile rank variables for these ratios. We re-estimate equation (2) using the decile ranks, one at a time, as the cross-sectional variable. On average, construction loans comprise 10% of the loan portfolio, while commercial loans, residential mortgages, and consumer loans make up 47%, 27%, and 7% of total loan balance, respectively.[12]

Table 4 reports the regression results. Column (1) estimates the effect of construction loan shares. The key variable of interest is the triple interaction, which measures how much loan loss provisioning asymmetry changes for a one-decile increase in construction loan share. As predicted, the coefficient on the triple interaction is negative and significant, consistent with greater asymmetry for banks with larger shares of construction loans. According to the point estimates, a one-decile increase in construction loan share is associated with 0.014 increase in asymmetry. To provide perspective, firms in the bottom decile of construction loan share distribution have asymmetric timeliness of -0.026 (0.039 - 0.135 × 1), firms in the decile just below the median have asymmetric timeliness of 0.028 (0.039 - 0.135 × 5), and firms in the top decile have asymmetric timeliness of 0.096 (0.039 - 0.135 ×10).

The results in column (2) show that commercial loan share does not affect asymmetric timeliness. This nil result could be because both commercial real estate loans and commercial and industrial loans are typically collateralized by assets such as real estate, equipment, inventory and

[12] Note that those ratios do not add to one because banks also hold agricultural loans, loans to foreign governments and other loans that collectively represent a small share of total loan balance.

accounts receivables. Thus, even if principal and interest payments fall behind, banks need not impair these loans as long as they are adequately collateralized (i.e., the fair value of the underlying collateral at least equals the present value of future cash flows of the loan).

Columns (3) and (4) show that asymmetric timeliness is mitigated when banks' portfolios include more residential real estate loans and consumer loans, consistent with valuation allowances for homogenous loan pools varying more linearly with changes in nonperforming loans. For example, the point estimates in column (3) imply that holding other things constant, firms in the bottom decile of residential mortgage share have asymmetric timeliness of 0.068 (= -0.073 + 0.005 × 1), whereas firms in the top decile have asymmetric timeliness of 0.023 (= -0.073 + 0.005 × 10), a reduction of 66% (= 1 - 0.023/0.068).

The results in Table 4 are consistent with conditional conservatism driving asymmetric timeliness of loan loss provision, by showing that the asymmetry is greatest when banks' loan portfolio is comprised of more high-risk construction loans that are individually evaluated for impairment and smallest when banks have more homogenous consumer and residential real estate loans that are tested in pools.

5.3 The incremental effect of loan portfolio duration

We next analyze the implications of cash flow horizons for loan impairment decisions. Banker et al. (2017) report that the usefulness of a loss indicator in assessing asset impairment depends on the indicator's ability to predict cash flows over the asset's life—e.g., sales change better predicts write-downs of (finite-lived) tangible assets, whereas stock return is more informative for (indefinite-lived) goodwill. Nonperforming loans are a lagged indicator for borrower repayment performance, and thus, are likely to be more informative in assessing shorter duration loans. For example, an increase in delinquent loans is likely to better predict the cash flows of loans over a shorter horizon than cash flows for long-horizon loans, such as a 30-year fixed rate mortgage.

We measure bank's loan portfolio duration in two ways. First, we construct a bank-specific measure of the sensitivity of a bank's loan interest income to changes in the Fed funds rate, which we label as loan interest beta (*INTBETA*).[13] Following Drechsler, Savov and Schnabl (2018), we estimate the loan interest beta by regressing the change in each bank's interest income rate (loan interest income divided by assets) on concurrent and three lags of change in the Fed funds rate. We then sum the coefficients to obtain a bank-specific interest income beta. Higher interest income beta indicates greater sensitivity of loan interest income to federal funds rate change and, therefore, reflects a shorter-duration loan portfolio.

Second, we construct a bank-quarter measure of the proportion of loans maturing or repricing within a year, labeled as *REP1YR*. The mean *REP1YR* in the sample is 0.436 with a standard deviation of 0.17, indicating that loans repricing or maturing within 1 year comprise 43.6% of a bank's loan portfolio on average. We code both *INTBETA* and *REP1YR* as decile rank variables, which we use as the cross-sectional variables when estimating equation (2).

Table 5 present estimates of the incremental effect of loan portfolio duration. Column (1) employs *INTBETA* as the cross-sectional variable. As predicted, the coefficient on $D\Delta NPL \times NPL \times INTBETA$ is negative and significant, suggesting that loan loss provision asymmetry is greatest when banks have higher interest income sensitivity. The estimates indicate that firms in the top decile of the interest beta distribution have asymmetric loan loss provisioning

[13] Loan interest beta is an important metric used by managers, investors and regulators to analyze a bank's interest income sensitivity which depends in large part on the bank's loan portfolio mix. Typically, loan portfolios pivoted more heavily towards shorter-term loans have higher interest beta, which means increases in short-term interest rates such as federal funds rate more quickly flow to loan interest rates charged, directly affecting the bank's earnings. The average interest income beta in the sample is 0.38 with a standard deviation of 1.41, which implies that, on average, bank interest income increases by 38 basis points (bps) per 1% increase in the Fed funds rate.

of 0.074 (= -0.014 - 0.006 × 10), which is almost four times as large as the asymmetric loan loss provisioning in the bottom decile (= -0.0.014 - 0.006). Column (2) shows similar effects using the proportion of loans maturing or repricing within a year as the cross-sectional variable. We find that loan loss provision asymmetry is 0.072 (= -0.012 - 0.006 × 10) when the proportion of loans maturing or repricing within one year is in the top decile of the distribution, a threefold increase relative to that in the bottom decile (= -0.012 - 0.006).

5.4. Economic Recessions, Q4, and Public Banks

We run more tests to better understand the conditional conservatism in loan loss provisions. First, we assess whether the asymmetry is more pronounced during economic downturn, when a greater focus on downside risk motivates both management and auditors to recognize bad news more quickly than good news (Jenkins, Kane and Velury 2009; Gunn, Khurana, and Stein 2018). When broad economic conditions are tough, banks' ability to collect principal and interest payments in full becomes questionable. Additionally, economic stress puts downward pressure on the fair values of collateral securing loans, increasing probable loan losses. Therefore, loan loss provisions are expected to be more conservative during economic downturns. We code an indicator variable *RECESSION* denoting the two economic recessions that occurred during our sample, as defined by the National Bureau of Economic Research (NBER).[14] The first one was between March 2001 and November 2001, and the second one was between December 2007 and June 2009.

Table 6 Column (1) reports the results of estimating the incremental effect of economic recessions on asymmetric linearity in loan loss provisioning. The point estimates suggest that, compared to an asymmetric timeliness of 0.026 during economic expansions, asymmetric timeliness is about 3.6 times as large during economic recessions at 0.121 (= -0.026 - 0.095). This

[14] The recession dates are reported in the NBER's US Business Cycle Expansions and Contractions: http://www.nber.org/cycles.html.

result is consistent with our prediction that asymmetry is more pronounced during tough economic times when management establishes allowances for loan losses more conservatively.

We next evaluate whether loan loss provision asymmetry is greater in the fourth quarter. Prior research reports that fourth quarter earnings exhibit greater asymmetric timeliness of bad news recognition due mainly to auditors' legal liability (Basu, Hwang, and Jan 2002). If the observed asymmetry is driven by the effects of conditional conservatism, then we expect the asymmetry to be greater in the fourth quarters. Table 6 column (2) reports the test. We create a fourth quarter dummy, Q4, and interact it with the asymmetric linear term. Because asset writedowns are typically more frequent and larger in the fourth quarter (Elliott and Shaw 1988, Fried, Schiff and Sondhi 1989, Jones and Bublitz 1990, Zucca and Campbell 1992, and Elliott and Hanna 1996), it is especially important to control for current-quarter *NCO*. *LLP* asymmetry in the fourth quarter is 0.107 (=0.030 + 0.077), which is more than thrice that in the interim quarters (0.030). Consistent with prior conservatism research, we find that *LLP* asymmetry is accentuated in the fourth quarter.

Figure 5 plots the time series of *LLP* asymmetry for Q4 and interim quarters. *LLP* asymmetry was stronger for Q4 during most of the sample period. Due to increasing loan impairments in adverse economic environments, the gap in *LLP* asymmetry between Q4 and interim quarters widened during the 2007-2008 financial crisis.

We also predict that the *LLP* asymmetry is greater for public banks. Relative to private banks, public banks face more external scrutiny from public equity holders, securities regulators (i.e., the U.S. Securities and Exchange Commission) and shareholder class-action lawsuits. The asymmetric timeliness of bad news recognition is higher among public firms than private firms due to public market demand for conditional conservatism (Ball and Shivakumar 2005, 2008; Nichols et al. 2009; Hope, Thomas, and Vyas 2013).

In column (3), we define public banks as those whose equity shares are traded on U.S. stock exchanges. We code a dummy variable *PUBLIC* equal to one for public banks. The coefficient on $D\Delta NPL \times \Delta NPL \times PUBLIC$ is negative and significant, suggesting that asymmetric timeliness of loan loss provisions for nonperforming loan increases is greater for public banks. Specifically, the asymmetric coefficient increases threefold from 0.029 for private banks to 0.093 for public banks (= -0.029 - 0.064).

6. Implications for loan loss provisioning research

In this section, we evaluate the specification and power of four competing loan loss provision models. We first examine the degree of misspecification (Type I error rate) using simulations similar to Kothari et al. (2005) and Collins et al. (2017), and next examine the models' power to detect provisioning management (Type II error rate). The four models differ in whether they control for concurrent loan charge-offs and (or) piecewise linearity, which we have shown to be critical components of the "normal" loan loss provisioning process.

6.1 Model specification

We first randomly select 100 bank-quarter observations from the aggregate sample of 79,070 observations following the simulation strategy of Kothari et al. (2005). Since those firms are randomly selected, one can reasonably assume there is no systematic provisioning management in the sample, i.e., the null hypothesis of no provisioning management is true. Thus, findings of significant discretionary *LLP* suggest model misspecification. We estimate each of the four competing models using the full sample and test for provisioning management in the subsample bank-quarters. Given that *LLP* is piecewise linear in ΔNPL, we also perform the analysis for stratified subsamples, where 100 bank-quarter observations are drawn from a particular quintile *ΔNPL* partition. We repeat this sampling procedure 250 times with replacement. Collins et al. (2017) argue that the random sample should be larger and more diverse across partitions. Following Collins et al. (2017), we alternatively draw 2,000 bank-quarters from the aggregate sample, and in the case of stratified random samples, we select 1,000 observations from a given *ΔNPL* partition and 1,000 from the remaining partitions.

Table 7 summarizes the simulation results. Panel A (B) reports the frequency with which the null hypothesis of no provisioning management is rejected at the 5% level against the alternative of positive (negative) discretionary loan loss provisions. With 250 simulations, there is a 95% probability that the rejection rate lies between 2.4% and 8.0% if the discretionary *LLP* measures are well-specified and the null is true. When observations are drawn from the aggregate sample, all models are relatively well-specified. This is not surprising because biases within *ΔNPL* partitions likely cancel out when samples are drawn across the entire distribution of *ΔNPL*. One exception is for tests using models that do not control for *NCO*, where the rejection rates for negative discretionary *LLP* are moderately high at about 12.8%.

As would be expected from Figure 1, the linear model excluding *NCO* has excessively high rejection rates in favor of positive discretionary *LLP* in both bottom and top *ΔNPL* quintiles, with rejection rates as high as 54.8% (92.2%) when 100 (2,000) observations are drawn. The model also displays excessively high rejection rates in favor of negative discretionary *LLP* for firms in the middle three *ΔNPL* quintiles, with rejection rates as high as 66% (77%) when 100 (2,000) observations are drawn. Adding piecewise linearity in the model substantially alleviates misspecification across partitions of *ΔNPL*. For example, the rejection frequencies are 2.4% (1.2%) and 2.8% (3.6%) for firms in the bottom and top *ΔNPL* quintile when 100 (2,000) observations are drawn. Turning to the linear model controlling for *NCO*, we see that the discretionary *LLP* measures are generally well-specified, except for a few cases where moderately high type I error rates occur. For example, the model rejects the null in favor of positive (negative) discretionary *LLP* 14.4% (14%) of the time for firms in the bottom (fourth) *ΔNPL* quintile when the random sample size is 2,000. Adding asymmetry in the model moderates the Type I error rates. For example, rejection frequencies drop from 14.4% (14%) to 4.8% (6.0%) for firms in the bottom (fourth) *ΔNPL* quintile when the alternative hypothesis is that discretionary *LLP* is positive (negative).

We conclude that models controlling for concurrent *NCO* and (or) asymmetry with respect to *ΔNPL* are better specified than linear models excluding *NCO.* This finding reinforces our assertion that, at a minimum, researchers should control for *NCO* in estimating *LLP*. The simulation analysis shows that, in most instances, the piecewise linear model including *NCO* tends to yield the lowest Type I error rates.

6.2 Power of Alternative Models to Detect Earnings Management

We next compare the four models' power in detecting earnings management. Following the procedure of Kothari et al. (2005), we randomly draw 100 bank-quarters from either the aggregate sample or from a given *ΔNPL* partition. We artificially induce earnings management in the selected bank-quarters by seeding positive or negative discretionary *LLP* that are 1, 3, or 5 basis points (bps) of beginning loans. We estimate each of the four models using all 79,070 observations and perform one-tailed *t*-tests for discretionary *LLP* at a significance level of 5% in the seeded observations. This simulation is repeated 250 times.

Table 8 Panel A reports the frequency with which the null hypothesis of no earnings management is rejected in favor of positive discretionary *LLP* among the 250 simulation tests.

When only 1 bps of total loans are seeded, all models have relatively low test power. The piecewise linear model with (without) *NCO* detects the discretionary *LLP* 13.6% (6.4%) of the time, while the linear model with (without *NCO*) detects only 12.8% (7.2%) of the time. Model power improves substantially once the seed level reaches 3 bps of total loans. The linear model without *NCO* detects 28.8% of the time, while the piecewise linear model without *NCO* detects 31.2% of the time, an 8.3% improvement. Controlling for *NCO* in the piecewise linear model, detection rate almost doubles to 67.2%. Once the seed level increases to 5 bps, models controlling for *NCO* almost always reject the null, with or without the piecewise linear term. Alternatively, the linear models and piecewise linear models without *NCO* reject 78.4% and 81.6% of the time.

The linear model without *NCO* has high power for detecting discretionary *LLP* for firms in the bottom and top *ΔNPL* quintiles. For example, the model can detect +1, +3, +5 bps *LLP* about 70.4%, 92.8%, and 99.6% of the time. Comparatively, the piecewise linear model with (without) *NCO* can detect +1, +3, +5 bps *LLP* about 16.4%, 49.2%, 89.6% of the time. The relatively high rejection rates for the linear model without *NCO* is due mainly to the excessive type 1 error rates (rather than greater power) of the model for firms with extreme *ΔNPL*. Importantly, controlling for *NCO* in both the linear and piecewise linear models improves model specification significantly without sacrificing test power across *ΔNPL* partitions. For example, the piecewise linear model with *NCO* can detect a 5 bps *LLP* about 89% (70%) of the time for firms in the bottom (top) *ΔNPL* quintile and 100% of the time for firms in the other three quintiles.

6.3 Replication of loan loss provisioning in the 1990s Boom - Liu and Ryan (2006)

The specification tests indicate that failure to control for concurrent *NCO* biases *LLP* estimates for both extreme and moderate *ΔNPL*. Liu and Ryan (2006) find that, during the 1990s economic booms, banks accelerated loan loss provisions to smooth earnings, and that this behavior is more pronounced for more profitable banks with more homogenous loans. Their *LLP* model does not include concurrent *NCO* as a determinant. This omission can lead to biased inferences concerning loan loss provisioning behavior in their setting, when nonperforming loans decreased sharply in a favorable economic environment (the average *ΔNPL* is -3.8 bps from 1990 to 2000, the boom period covered by Liu and Ryan (2006)).

We first replicate the tests in Table 2 of Liu and Ryan (2006). We follow their sampling procedure and retain bank-year observations from the intersection of the Compustat Bank Annual database and the FR Y-9C reports for bank holding companies between 1991 and 2000. For comparability, we construct the variables based on their definitions. Table 9, column (1) reports the replication results. The variables of interest are earnings before provisions (*X)* interacted with a dummy for above-median return on assets (*HIGHROA*), and earnings before provisions (*X)* interacted with the percentage of homogenous loans in the loan portfolio (*HOM%*). Consistent with Liu and Ryan (2006), we find that these two interaction terms are significantly positive, suggesting that the association between loan loss provisions and earnings before loan loss provisions are more positive for more profitable banks and for banks with more homogenous loans. Given this finding, one might reasonably infer like Liu and Ryan (2006) that those banks smoothed income more through provisions during economic booms.

We modify Liu and Ryan's (2006) model by incorporating the *LLP* asymmetry with respect to *ΔNPL*. As shown in column (2), *ΔNPL×DΔNPL* has a significantly negative coefficient, verifying *LLP* asymmetry absent controls for *NCO*. Although the two interaction terms become smaller, they remain positive and significant. This is not the case, however, once we include *NCO* in the model. Columns (3) and (4) show that once *NCO* is controlled for, bank profitability and the proportion of homogenous loans are no longer positively associated with bank earnings smoothing.

We also note that the asymmetry term, *ΔNPL×DΔNPL*, is insignificant once *NCO* is included in the model, which is likely due to a sampling issue as we lose a significant number of banks when merging the Compustat Bank dataset with FR Y-9C reports.[15] In summary, controlling for concurrent *NCO* in the *LLP* model calls into question Liu and Ryan's (2006) inference regarding banks' loan loss provisioning behavior during economic booms.

7. Conclusion

The standard approach in modelling loan loss provisions is based on linear projections of loan loss provisions on changes in loan portfolio quality observable to the researcher (i.e., changes in nonperforming loans). An implicit assumption is that loan loss provisions change proportionally to changes in nonperforming loans. This linearity assumption, we find, is strongly rejected by large-sample data. Given the observed data patterns and the accounting and regulatory guidance for loan loss accruals, we propose a piecewise linear specification that accommodates asymmetric loan loss provisioning. Our model yields two key findings. First, failing to control for the mechanical accounting effects of loan charge-offs on nonperforming loans and allowance for loan losses induces severe nonlinearity (a V-shaped curve), where loan loss provisions *increase* proportionally to decreases in nonperforming loan. Second, after controlling for loan charge-offs, loan loss provisions move in the same direction as nonperforming loan change, with loan loss provisions changing more with nonperforming loan increases than with nonperforming loan decreases.

We show that the residual asymmetry is at least partly due to conditional conservatism. We find that the asymmetric nonlinearity is greatest when banks' loan portfolio is comprised of more

[15] In untabulated analysis, we verify that using only the Compustat Bank dataset or only FR Y-9C reports financial data, the asymmetric nonlinear term is negative and significant for the period 1991-2000, when we include controls for *NCO*. We note that the restricted sample used in Table 11 is unlikely to lead to the insignificant results for the two interaction terms because, when *NCO* is excluded, those two terms are highly significant.

high-risk construction loans that are individually impaired and smallest when banks have more homogenous consumer and residential real estate loans that are tested in pools. We also show that the loan loss provision asymmetry is greater for banks with shorter-maturity loan portfolios, consistent with changes in nonperforming loans being a more relevant indicator for unrealized credit losses over a shorter time horizon. The nonlinearity in loan loss provisioning is also more pronounced when banks larger concurrent charge-offs, are publicly traded, in the fourth quarter and during recessions, all consistent with conditional conservatism playing an important role in loan loss provisioning.

Appendix A

Variable Definitions

Variable	Definition
LLP	Loan loss provisions (BHCK4230) scaled by lagged loans (BHCK2122).
ΔNPL	Change in nonperforming loans (BHCK5525+BHCK5526) scaled by lagged loans.
SIZE	Logarithm of lagged total assets (BHCK2170).
ΔLOAN	Change in loan (BHCK2122) scaled by lagged loans.
ALL	Allowance for loan losses (BHCK3123) scaled by lagged loans.
NCO	Net charge-offs (BHCK4635-BHCK4605) scaled by lagged loans.
ΔNONACC	Change in nonaccrual loans (BHCK5526) scaled by lagged loans.
ΔACC	Change in accruing loans 90 days or more past due (BHCK5525) scaled by lagged loans.
ΔNPLNCO	Change in nonperforming loans (BHCK5525+BHCK5526) plus net charge-offs (BHCK4635-BHCK4605) scaled by lagged loans.
CONSTRUCTION	The ratio of construction loans (BHCKF158+BHCKF159) to total loans (BHCK2122).
COMMERCIAL	The ratio of non-construction commercial loans (BHCK1460+BHCK1763+BHCK1764) to total loans (BHCK2122).
RESIDENTIAL REAL ESTATE	The ratio of residential real estate mortgage loans (BHCK1797+BHCK5367+BHCK5368) to total loans
CONSUMER	The ratio of consumer loans (BHCKB538+BHCKB539+BHCKK137+BHCKK207) to total loans
INTBETA	The sensitivity of loan interest income to changes in Fed funds rate, calculated by regressing the change in a bank's interest income rate on the contemporaneous and three lagged quarterly changes in the Fed funds rate. Interest beta is the sum of the coefficients on the four changes in the Fed funds rate. Interest income rate is calculated as quarterly interest income divided by quarterly average assets and then annualized (multiplied by four).
REP1YR	Loans maturing or repricing within 1 year (RCONA564+RCONA565 +RCFDA570+RCFDA571) as a proportion of total loans. Loan repricing data are from commercial bank call reports (FFIEC 031/041 forms) and are aggregated to the holding company level using financial high holder ID RSSD9364.
RECESSION	An indicator variable denoting economic recessions during the sample period. According to NBER, the first one was between March 2001 and November 2001, and the second one was between December 2007 and June 2009
Q4	An indicator for fourth quarter.
PUBLIC	An indicator for public banks, defined as those whose equity shares are traded on U.S. stock exchanges. Public banks are identified via the RSSD (bank regulatory identification number)-PERMCO (permanent company number used by CRSP) link table provided by Federal Reserve Bank of New York.

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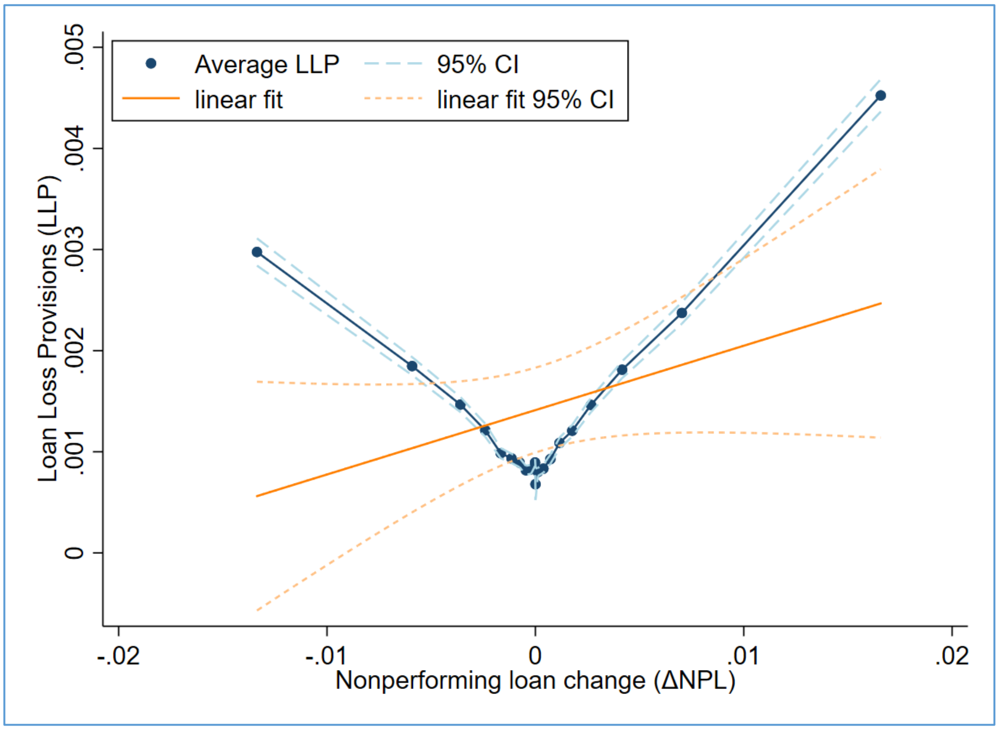
FIGURE 1

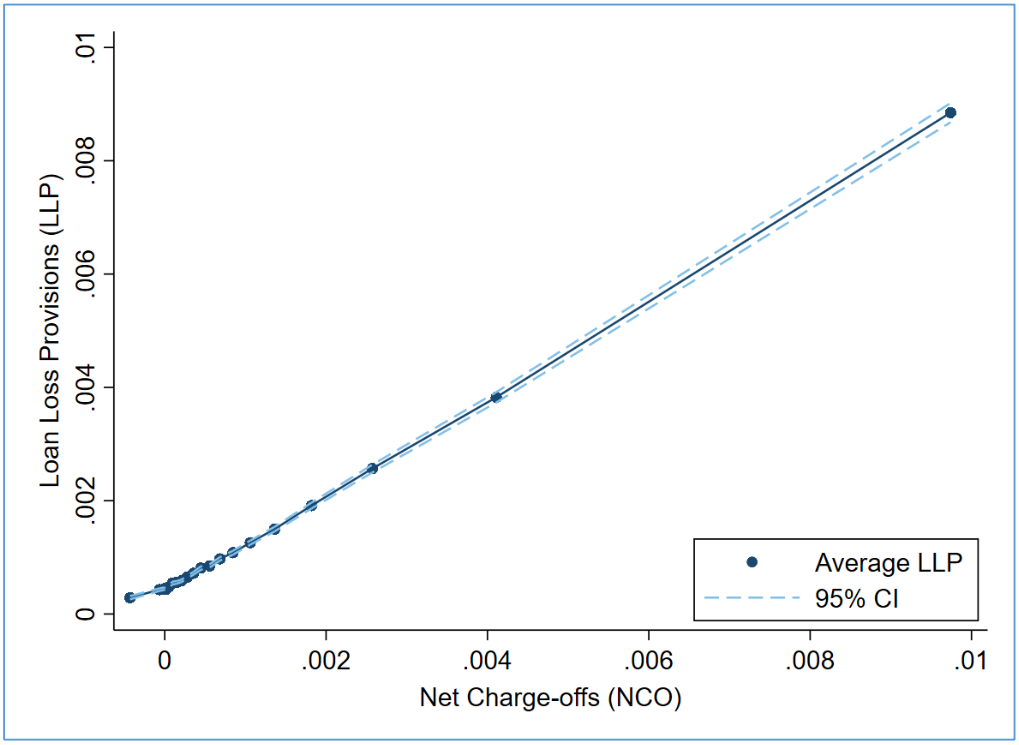
Unconditional Relation Between LLP and ΔNPL (Raw Data)



This figure presents a binned scatter plot of the relationship between quarterly loan loss provisions and quarterly change in nonperforming loans. To construct this figure, we divide quarterly change in nonperforming loan (scaled by beginning-of-the-quarter loans) into 20 equal-sized (quantile) bins and plot the mean loan loss provisions versus the mean change in nonperforming loans (both scaled by beginning loans) by quantile bins. The light blue dashed lines represent the 95% confidence interval of loan loss provisions within each quantile bin. The orange line represents the OLS fit for the scatter plot, and the light orange dashed lines represent the 95% confidence interval for the OLS fit.

FIGURE 2

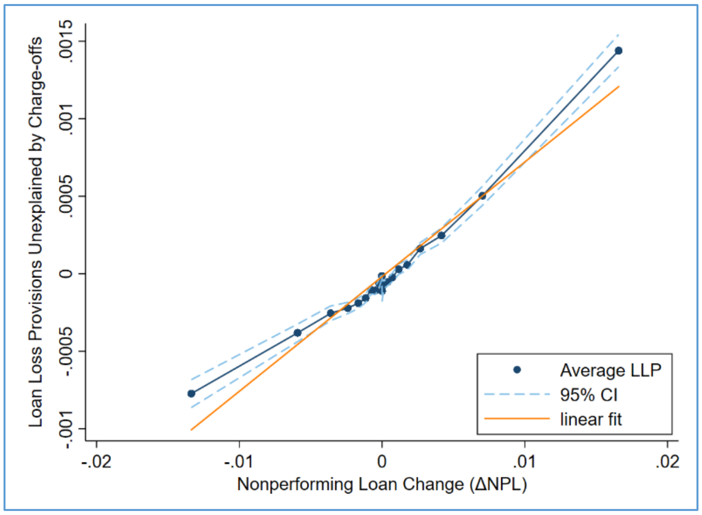
Unconditional Relation Between LLP and NCO (Raw Data)



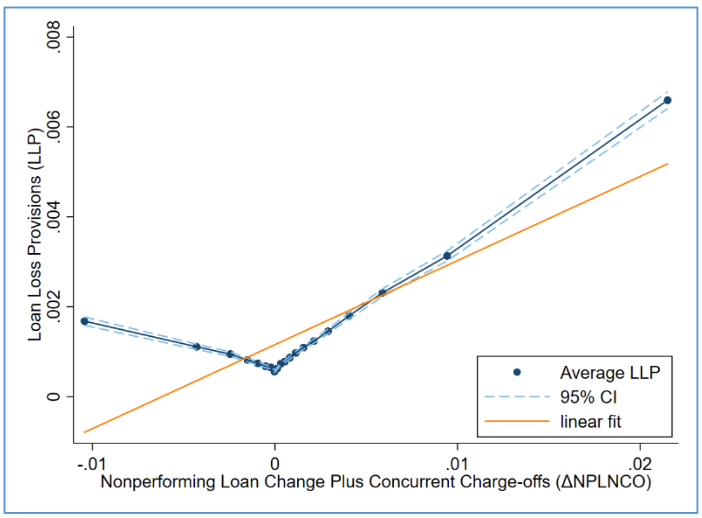
This figure presents a binned scatter plot of the relationship between quarterly loan loss provisions and net loan charge-offs. To construct this figure, we divide quarterly net charge-offs (scaled by beginning-of-the-quarter loans) into 20 equal-sized (quantile) bins and plot the mean loan loss provisions versus the mean net loan charge-offs (both scaled by beginning loans) by quantile bins. The light blue dashed lines represent the 95% confidence interval of loan loss provisions within each quantile bin.

FIGURE 3

Controlling for the Effects of Concurrent Loan Charge-offs



Panel A: Loan Loss Provisions Unexplained by Charge-offs

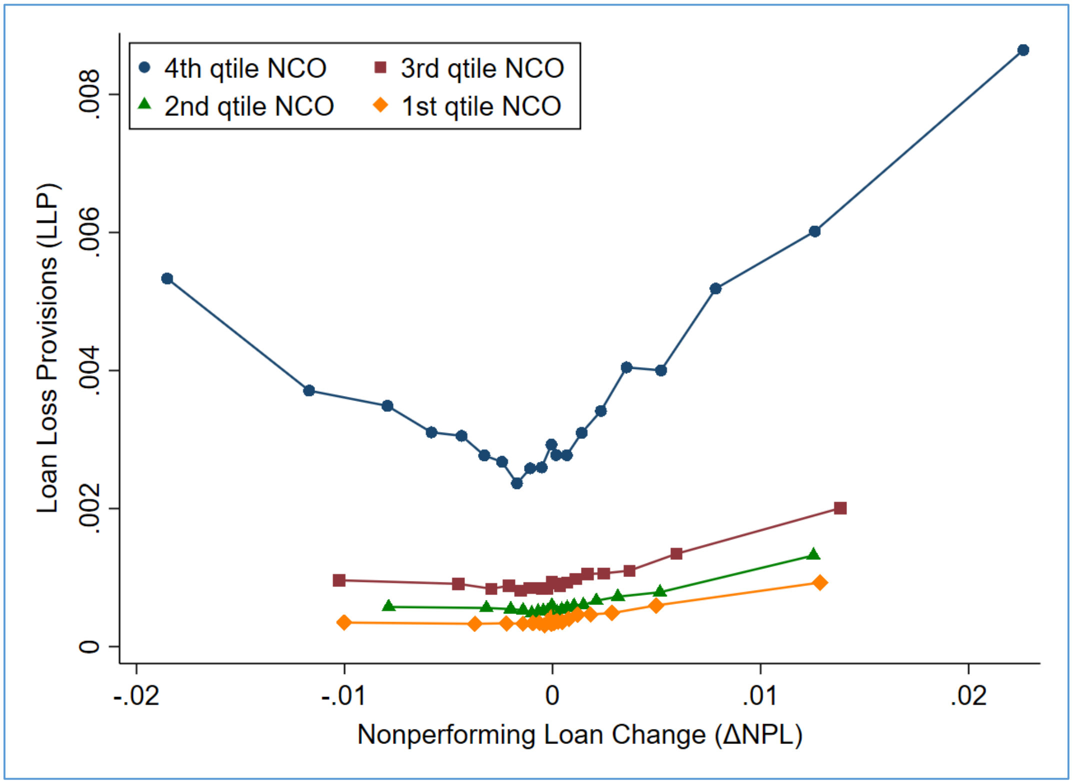


Panel B: Nonperforming Loan Change Plus Charge-offs

The figures plot the relationship between loan loss provisions and nonperforming loan change, controlling for the effects of loan charge-offs in two alternative ways. Panel A presents a binned scatter plot of the mean loan loss provisions unexplained by loan charge-offs versus mean nonperforming loan change (both deflated by beginning loan balance) across 20 (equal-frequency) quantile bins by nonperforming loan change. The unexplained portion of loan loss provisions is derived from the residuals of the regression of loan loss provisions on concurrent loan charge-offs. Panel B presents a binned scatter plot of the mean loan loss provisions against mean nonperforming loan change plus concurrent loan charge-offs (both deflated by beginning loan balance) across 20 (equal-frequency) quantile bins by nonperforming loan change plus loan charge-offs.

FIGURE 4

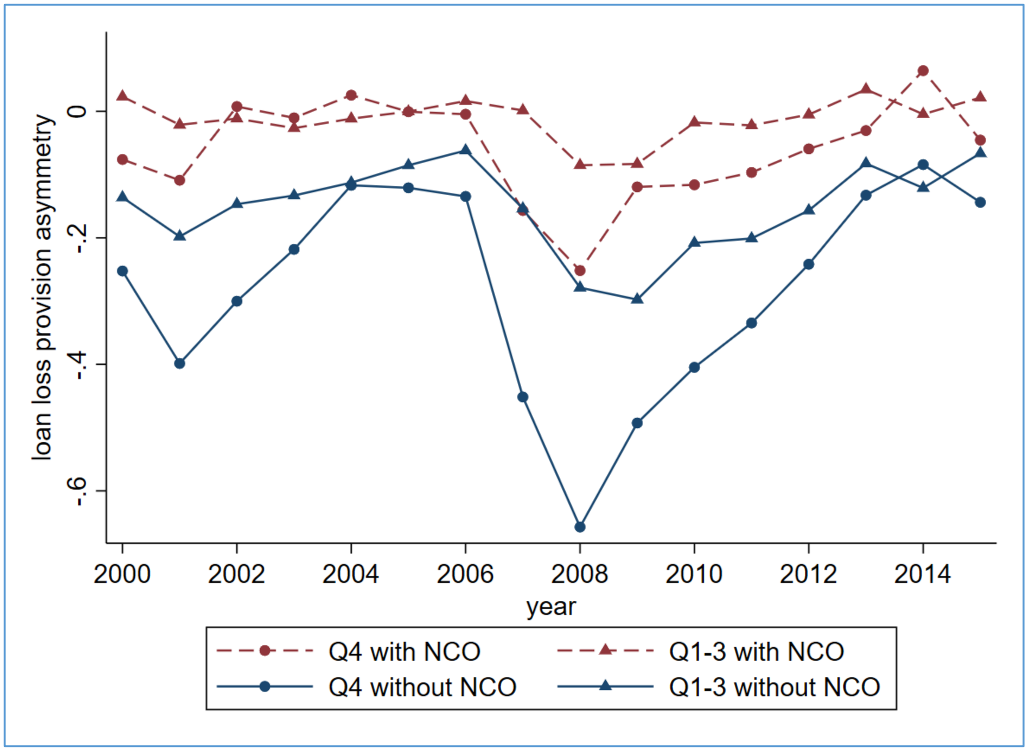
LLP vs *ΔNPL* Conditional on *NCO*



This figure plots the interactive effects of net loan charge-offs (NCO) on asymmetry loan loss provisions for nonperforming loan increases versus decreases. To construct this figure, we the sample into quartiles based on *NCO*, and within each *NCO* quartile we further divide observations into 20 equal-frequency (quantile) bins by nonperforming loan change (*ΔNPL*). We create a binned scatter plot of mean loan loss provisions against mean loan charge-offs (both scaled by beginning loans) within each *NCO* quartile.

FIGURE 5

LLP Asymmetry for Q4 and Interim Quarters Over Time



The figure plots *LLP* asymmetry for fourth quarter and interim quarters over the sample period. We run the following regression by year:

$$LLP_{it} = \beta_0 + \beta_1 D\Delta NPL_{it} + \beta_2 \Delta NPL_{it} + \beta_3 D\Delta NPL_{it} \times \Delta NPL_{it} + \beta_4 D\Delta NPL_{it} \times Q4 + \beta_5 \Delta NPL_{it} \times NCO_{it} + \beta_6 D\Delta NPL_{it} \times \Delta NPL_{it} \times Q4 + \beta_7 Q4 + \chi'_{it} + \epsilon_{it}$$

where *Q4* is an indicator variable for fourth quarter of the year. Coefficient β_3 represents *LLP* asymmetry for Q1-Q3 of each year, and coefficient β3+β6 represents *LLP* asymmetry for Q4 each year. Red-dashed lines represent *LLP* asymmetry estimates obtained from the model controlling for *NCO*, and blue-solid lines represent *LLP* asymmetry estimates obtained from the model excluding NCO. Circles represent Q4 *LLP* asymmetry, and triangles represent interim quarters *LLP* asymmetry.

TABLE1

Summary Statistics

Panel A: Descriptive Statistics (N = 79,070)

	Mean	Std	p25	Median	p75
LLP_t	0.14%	0.26%	0.03%	0.07%	0.14%
ΔNPL_{t+1}	0.03%	0.58%	-0.14%	0.00%	0.14%
ΔNPL_t	0.03%	0.57%	-0.14%	0.00%	0.14%
ΔNPL_{t-1}	0.03%	0.57%	-0.13%	0.00%	0.14%
ΔNPL_{t-2}	0.03%	0.55%	-0.13%	0.00%	0.14%
$\Delta LOAN_t$	2.01%	4.53%	-0.49%	1.57%	3.84%
NCO_t	0.12%	0.23%	0.01%	0.04%	0.12%
ALL_{t-1}	1.52%	0.67%	1.11%	1.36%	1.72%
$SIZE_{t-1}$	13.65	1.39	12.68	13.37	14.12

Panel B: Pearson/Spearman Correlations

	LLP_t	ΔNPL_{t+1}	ΔNPL_t	ΔNPL_{t-1}	ΔNPL_{t-2}	NCO_t	ALL_{t-1}	$\Delta LOAN_t$	$SIZE_{t-1}$
LLP_t		**0.037**	**0.088**	**0.120**	**0.127**	**0.612**	**0.198**	**-0.091**	**0.128**
ΔNPL_{t+1}	**0.078**		0.002	**0.047**	**0.044**	**-0.023**	**-0.110**	**0.060**	0.003
ΔNPL_t	**0.146**	**0.039**		0.001	**0.044**	**-0.059**	**-0.092**	**0.067**	0.006
ΔNPL_{t-1}	**0.174**	**0.064**	**0.034**		-0.002	**0.075**	**-0.039**	**-0.006**	**0.009**
ΔNPL_{t-2}	**0.176**	**0.048**	**0.056**	**0.029**		**0.078**	**-0.040**	**-0.036**	**0.006**
NCO_t	**0.797**	-0.006	**-0.025**	**0.120**	**0.138**		**0.313**	**-0.261**	**0.211**
ALL_{t-1}	**0.359**	**-0.105**	**-0.080**	0.000	-0.005	**0.503**		**-0.206**	**0.149**
$\Delta LOAN_t$	**-0.161**	**0.038**	**0.085**	**-0.018**	**-0.050**	**-0.243**	**-0.218**		**-0.062**
$SIZE_{t-1}$	**0.128**	**0.009**	**0.012**	**0.014**	**0.013**	**0.147**	**0.126**	**-0.024**	

This table presents summary statistics for the variables used in the main regression analyses. Panel A reports the descriptive statistics of the variables and Panel B reports the Pearson (Spearman) correlations between the variables below (above) the diagonal. Bold face indicates significance level at the 10% level in two-tailed tests. Variable definitions are in the Appendix

TABLE 2

Loan Loss Provisions Models

Panel A: Linear models (N = 79,070)

		LLP				
		(1)	(2)	(3)	(4)	(5)
ΔNPL_{t+1}		0.015***	0.017***	0.014***	0.019***	0.019***
		(5.29)	(6.42)	(5.55)	(7.69)	(9.81)
$\boldsymbol{\Delta NPL_{t}}$	**+**	**0.050*** **	**0.046*** **	**0.042*** **	**0.047*** **	**0.057*** **
		(15.70)	**(15.00)**	**(14.44)**	**(16.57)**	**(25.79)**
ΔNPL_{t-1}	+	0.057***	0.049***	0.044***	0.043***	0.023***
		(20.06)	(17.59)	(16.85)	(16.66)	(12.23)
ΔNPL_{t-2}	+	0.058***	0.047***	0.042***	0.041***	0.016***
		(21.13)	(17.72)	(16.58)	(17.10)	(8.94)
$SIZE_{t-1}$		0.000***	0.000***	0.000***	0.001***	0.000***
		(6.03)	(5.75)	(6.19)	(8.16)	(6.25)
$\Delta LOAN_{t}$		-0.007***	-0.005***	-0.004***	-0.003***	0.000**
		(-19.28)	(-14.45)	(-14.58)	(-12.31)	(2.14)
ΔGDP_{t}		0.013***				
		(7.85)				
ΔCS_{t}		-0.026***				
		(-23.41)				
$\Delta UNEMPLOY_{t}$		0.003***				
		(9.67)				
ALL_{t-1}	-				0.079***	-0.044***
					(17.10)	(-14.66)
$\boldsymbol{NCO_{t}}$	**+**					**0.792*** **
						(85.97)
Bank FE		No	No	Yes	Yes	Yes
Year-Quarter FE		No	Yes	Yes	Yes	Yes
Adj. R^2		0.157	0.225	0.404	0.446	0.701
Adj. within bank R^2				0.28	0.3	0.628
AIC		-733,270	-739,955	-763,531	-769,275	-818,040
BIC		-733,178	-739,751	-763,438	-769,183	-817,947

Panel B: Piecewise linear models (N = 79,070)

		LLP					
		(1)	(2)	(3)	(4)	(5)	(6)
ΔNPL_{t+1}		0.067***	0.067***	0.056***	0.053***	0.036***	0.050***
		(18.08)	(18.10)	(16.01)	(15.33)	(13.05)	(17.21)
ΔNPL_{t}	+	**0.136*** **	**0.129*** **	**0.119*** **	**0.115*** **	**0.073*** **	**0.155*** **
		(29.11)	**(27.79)**	**(26.47)**	**(25.98)**	**(20.68)**	**(37.64)**
ΔNPL_{t-1}	+	0.089***	0.080***	0.072***	0.064***	0.039***	0.071***
		(20.75)	(18.26)	(17.02)	(15.32)	(12.29)	(20.81)
ΔNPL_{t-2}	+	0.092***	0.074***	-0.079***	0.061***	0.023***	0.063***
		(20.93)	(16.72)	(-13.01)	(14.66)	(7.58)	(19.06)
$D\Delta NPL_{t+1} \times \Delta NPL_{t+1}$		-0.111***	-0.107***	-0.088***	-0.075***	-0.039***	-0.030***
		(-17.22)	(-17.05)	(-14.88)	(-12.69)	(-8.22)	(-5.13)
$D\Delta NPL_{t} \times \Delta NPL_{t}$	-	**-0.214*** **	**-0.195*** **	**-0.177*** **	**-0.164*** **	**-0.034*** **	**-0.153*** **
		(-28.06)	**(-26.09)**	**(-24.80)**	**(-23.22)**	**(-6.65)**	**(-23.16)**
$D\Delta NPL_{t-1} \times \Delta NPL_{t-1}$	-	-0.110***	-0.096***	-0.079***	-0.064***	-0.041***	-0.061***
		(-17.98)	(-15.30)	(-13.01)	(-10.41)	(-8.47)	(-10.32)
$D\Delta NPL_{t-2} \times \Delta NPL_{t-2}$	-	-0.123***	-0.093***	-0.076***	-0.063***	-0.024***	-0.067***
		(-18.46)	(-13.84)	(-12.28)	(-10.19)	(-5.26)	(-11.52)
$SIZE_{t-1}$		0.000***	0.000***	0.001***	0.001***	0.000***	0.000***
		(10.24)	(10.03)	(7.40)	(9.08)	(6.50)	(5.13)
$\Delta LOAN_{t}$		-0.003***	-0.002***	-0.003***	-0.002***	0.001***	-0.002***
		(-11.17)	(-7.82)	(-10.29)	(-8.76)	(4.27)	(-9.62)
ΔGDP_{t}		0.017***					
		(10.55)					
ΔCS_{t}		-0.012***					
		(-12.40)					
$\Delta UNEMPLOY_{t}$		0.004***					
		(14.19)					
ALL_{t-1}					0.047***	-0.054***	0.024***
					(9.94)	(-17.13)	(6.37)
$\boldsymbol{NCO_{t}}$						**0.760*** **	
						(78.31)	
Slope coefficient for nonperforming loan decreases							
$\Delta NPL_{t+1} + D\Delta NPL_{t+1} \times \Delta NPL_{t+1}$		-0.044***	-0.040***	-0.032***	-0.022***	-0.003	0.020***
$\boldsymbol{\Delta NPL_{t} + D\Delta NPL_{t} \times \Delta NPL_{t}}$		**-0.078*** **	**-0.066*** **	**-0.058*** **	-0.049***	**0.039*** **	**0.002**
$\Delta NPL_{t-1} + D\Delta NPL_{t-1} \times \Delta NPL_{t-1}$		-0.021***	-0.016***	-0.007	0.000	-0.002	0.010**
$\Delta NPL_{t-2} + D\Delta NPL_{t-2} \times \Delta NPL_{t-2}$		-0.031***	-0.019***	-0.011***	0.002	-0.001	-0.004
Bank FE		No	No	Yes	Yes	Yes	Yes
Year-quarter FE		No	Yes	Yes	Yes	Yes	Yes
adj. R-sq		0.272	0.332	0.468	0.473	0.709	0.543
Within adj. R				0.329	0.336	0.633	0.423
AIC		-744898	-751557	-772583	-773351	-820250	-778429
BIC		-744731	-750834	-772490	-773258	-820157	-778336

This table presents the results of the main regression analysis. Panel A estimates several linear specifications. Column (1) replicates model (a) in Beatty and Liao (2014). The model includes several macroeconomic variables: change in GDP over the quarter (*ΔGDP*), the return on the Case-Shiller Real Estate index over the quarter (*ΔCS*), and change in unemployment rates over the quarter (*ΔUNEMP*). Column (2) replaces the macroeconomic variables in column (1) with the more restrictive year-quarter fixed effects, and column (3) additionally controls for bank fixed effects. Column (4) includes beginning-of-period allowance for loan losses (*ALL*), which is similar to Model (c) in Beatty and Liao (2014). The last column controls for current-period loan charge-offs (*NCO*), which resembles model (d) in Beatty and Liao (2014). Panel B estimates piecewise linear specifications. *t*-statistics are reported in parentheses based on heteroscedasticity robust standard errors two-way clustered at the bank and year-quarter level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tail). See the Appendix for definitions of all variables in the regressions. The standalone *DΔNPL* variables are included in the regression. Since the coefficients on those variables all close to zero and insignificant, we do not report those coefficients to conserve space.

TABLE 3

The Incremental Effect of Loan Charge-offs (NCO)

		LLP
ΔNPL_t	+	0.054***
		(14.83)
$D\Delta NPL_t \times \Delta NPL_t$	-	-0.028***
		(-5.19)
Effect of Loan Charge-offs on the Recognition of *ΔNPL*		
$\boldsymbol{\Delta NPL_t \times NCO_t}$	+	**3.728*** **
		(3.74)
$\boldsymbol{D\Delta NPL_t \times \Delta NPL_t \times NCO_t}$	-	**-4.688** **
		(-2.48)
$SIZE_{t-1}$		0.000***
		(6.59)
$\Delta LOAN_t$		0.001***
		(4.61)
ALL_{t-1}		-0.054***
		(-17.15)
NCO_t		0.787***
		(52.69)
FE		Bank, Year-Quarter
N		79,070
Adj. R^2		0.705
Adj. within bank R^2		0.628

This table presents the results of estimating the effect of loan charge-offs on asymmetric loan loss provisioning. *NCO* is net charge-offs, defined as gross charge-offs minus recoveries, divided by lagged loans. *t*-statistics are reported in parentheses based on heteroscedasticity robust standard errors two-way clustered at the bank and year level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tail).

TABLE 4

The Effect of Loan Portfolio Composition

		Loan Portfolio Composition (*LPC*)			
		(1)	(2)	(3)	(4)
		Construction	Commercial	Residential Real Estate	Consumer
ΔNPL_t	+	0.019***	0.079***	0.090***	0.103***
		(2.63)	(10.39)	(13.16)	(14.38)
$D\Delta NPL_t \times \Delta NPL_t$	-	0.039***	-0.048***	-0.073***	-0.082***
		(3.43)	(-4.17)	(-7.22)	(-7.89)
Effect of Loan Portfolio Composition on the Recognition of ΔNPL					
$\Delta NPL_t \times LPC$	+	**0.009*** **	**-0.000**	**-0.003** **	**-0.006*** **
		(8.13)	**(-0.18)**	**(-2.24)**	**(-4.71)**
$D\Delta NPL_t \times \Delta NPL_t \times LPC$	-	**-0.014*** **	**-0.000**	**0.005*** **	**0.007*** **
		(-7.33)	**(-0.09)**	**(3.08)**	**(4.00)**
$SIZE_{t-1}$		0.000***	0.000***	0.000***	0.000***
		(7.28)	(8.62)	(8.19)	(8.40)
$\Delta LOAN_t$		0.001***	0.001***	0.000***	0.001***
		(3.58)	(3.01)	(2.98)	(3.36)
ALL_{t-1}		-0.049***	-0.049***	-0.049***	-0.050***
		(-15.91)	(-15.94)	(-15.81)	(-15.93)
NCO_t		0.771***	0.776***	0.775***	0.774***
		(80.59)	(81.04)	(80.60)	(80.35)
FE		Bank, Year-Quarter	Bank, Year-Quarter	Bank, Year-Quarter	Bank, Year-Quarter
N		79,061	79,022	79,045	78,879
Adj. R^2		0.704	0.702	0.703	0.702
Adj. within bank R^2		0.626	0.624	0.624	0.624

This table presents the results of estimating the effect of loan portfolio composition (LPC) on nonlinear loan loss provisioning. Column (1) uses as the ratio of construction loans divided by total loans as the cross-sectional variable, and column (2) uses non-construction commercial loans, which in commercial and include commercial and industrial loans and commercial real estate loans, divided by total loans. Column (3) uses residential mortgages divided by total loans. Column (3) uses consumers (excluding residential real estate mortgages), such as car loans and credit card loans, as a proportion of total loans. Each loan portfolio composition variable is converted to a decile rank variable. *t*-statistics are reported in parentheses based on heteroscedasticity robust standard errors two-way clustered at the bank and year level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tail).

TABLE 5

The Effect of Loan Portfolio Maturity

		Loan Portfolio Maturity	
		(1)	(2)
		Loan Interest Beta	Loans maturing/repricing within a year
ΔNPL_t	+	0.048***	0.051***
		(6.37)	(6.25)
$D\Delta NPL_t \times \Delta NPL_t$	-	-0.014	-0.012
		(-1.29)	(-1.08)
Effect of Loan Portfolio Maturity on the Recognition of ΔNPL			
$\Delta NPL_t \times LPM$	+	**0.005***	**0.004***
		(4.19)	**(3.34)**
$D\Delta NPL_t \times \Delta NPL_t \times LPM$	-	**-0.006***	**-0.006***
		(-3.20)	**(-3.59)**
$SIZE_{t-1}$		0.000***	0.000***
		(8.44)	(8.20)
$\Delta LOAN_t$		0.001***	0.001***
		(3.24)	(3.25)
NCO_t		0.775***	0.770***
		(80.24)	(76.39)
ALL_{t-1}		-0.049***	-0.053***
		(-15.97)	(-16.16)
FE		Bank, Year-Quarter	Bank, Year-Quarter
N		77,968	74,262
Adj. R^2		0.703	0.696
Adj. within bank R^2		0.625	0.616

This table presents the results of estimating the effect of loan portfolio maturity on asymmetry loan loss provisioning asymmetry. We use two variables to proxy for loan portfolio maturity. Column (1) uses loan interest income beta (*INTBETA*), which is defined as the sensitivity of loan interest income to change in Fed funds rate. To construct this measure, for each bank we regress the quarterly change in a bank's interest income rate on the contemporaneous and three lagged quarterly changes in the Fed funds rate. Interest beta is the sum of the coefficients on the four changes in the Fed funds rate. A greater interest beta indicates banks with lower maturity loan portfolio. Column (2) uses the proportion of loan portfolios repricing or maturing within a year (*MAT1YR*). Both variables are coded as decile ranks. *INTBETA* is time-invariant for each bank and therefore is subsumed by bank fixed effects. The coefficient on standalone *MAT1YR* close to zero and insignificant and thus is not tabulated. *t*-statistics reported in parentheses are two-way clustered at the bank and year level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tail).

TABLE 6

Economic Recessions, Q4 Reporting, and Public Banks

		VAR		
		(1)	(2)	(3)
		RECESSION	*Q4*	*PUBLIC*
ΔNPL_t	+	0.059***	0.066***	0.062***
		(15.43)	(17.28)	(15.48)
$D\Delta NPL_t \times \Delta NPL_t$	-	-0.026***	-0.030***	-0.029***
		(-4.80)	(-5.54)	(-4.91)
Effect of Recessions, Q4, and Public Banks on the Recognition of *ΔNPL*				
$\boldsymbol{\Delta NPL_t \times VAR}$	+	**0.061*** **	**0.050*** **	**0.053*** **
		(8.48)	**(6.24)**	**(7.12)**
$\boldsymbol{D\Delta NPL_t \times \Delta NPL_t \times VAR}$	-	**-0.095*** **	**-0.077*** **	**-0.064*** **
		(-7.71)	**(-6.65)**	**(-5.79)**
$SIZE_{t-1}$		0.000***	0.000***	0.000***
		(8.17)	(8.66)	(8.30)
$\Delta LOAN_t$		0.001***	0.000***	0.000**
		(3.15)	(2.95)	(2.27)
ALL_{t-1}		-0.048***	-0.049***	-0.050***
		(-15.61)	(-15.86)	(-16.28)
NCO_t		0.775***	0.773***	0.774***
		(80.60)	(80.18)	(81.40)
FE		Bank, Year-Quarter	Bank, Year-Quarter	Bank, Year-Quarter
N		79,070	79,070	79,070
Adj. R^2		0.703	0.703	0.703
Adj. within bank R^2		0.626	0.625	0.626

This table estimates the incremental effect of economic recessions, fourth quarter reporting, and public banks on asymmetric loan loss provisioning. In column (1), *RECESSION* is an indicator variable denoting economic recessions during the sample period. According to NBER, the first one was between March 2001 and November 2001, and the second one was between December 2007 and June 2009. The standalone RECESSION is subsumed by year-quarter fixed effects. In column (2), Q4 is an indicator variable for fourth quarter loan loss provisions. The standalone Q4 variable is omitted due to inclusion of year-quarter fixed effects. In column (3), *PUBLIC* is an indicator variable if the bank is publicly listed. The standalone *PUBLIC* is subsumed by bank fixed effects. *t*-statistics reported in parentheses are two-way clustered at the bank and year level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tail).

TABLE 7

Specification Tests of Earnings Management through LLP (Type I Error)

Panel A: H1: Discretionary LLP>0

	All banks	*ΔNPL Bottom*	*ΔNPL Q2*	*ΔNPL Q3*	*ΔNPL Q4*	*ΔNPL Top*
100 random bank-quarters following Kothari et al. (2005)						
Linear without *NCO (Table 2, Panel A, Column 4)*	2.8	**54.8**	***0.0***	***0.0***	***0.0***	**20.8**
Piecewise linear without *NCO (Table 2, Panel B, Column 4)*	3.6	2.8	2.4	4.4	2.8	2.4
linear with *NCO (Table 2, Panel A, Column 5)*	5.2	**10.0**	2.4	3.2	***0.8***	3.6
Piecewise linear with *NCO (Table 2, Panel B, Column 5)*	2.8	5.6	3.6	5.2	3.6	***1.6***
2000 random bank-quarters following Collins et al. (2017)						
Linear without *NCO (Table 2, Panel A, Column 4)*	5.2	**97.2**	***0.0***	***0.0***	***0.0***	**68.4**
Piecewise linear without *NCO (Table 2, Panel B, Column 4)*	5.6	3.6	3.6	6.0	3.6	***1.2***
linear with *NCO (Table 2, Panel B, Column 4)*	5.2	**14.4**	4.0	3.6	2.4	4.0
Piecewise linear with *NCO (Table 2, Panel B, Column 5)*	6.0	4.8	4.0	**10.0**	**10.4**	2.8

Panel B: H1: Discretionary LLP<0

	All banks	*ΔNPL Bottom*	*ΔNPL Q2*	*ΔNPL Q3*	*ΔNPL Q4*	*ΔNPL Top*
100 random bank-quarters following Kothari et al. (2005)						
Linear without *NCO (Table 2, Panel A, Column 4)*	**12.8**	***0.0***	**66.0**	**59.6**	**65.2**	***0.4***
Piecewise linear without *NCO (Table 2, Panel B, Column 4)*	**12.8**	**9.6**	**10.8**	5.2	**8.4**	**11.6**
linear with *NCO (Table 2, Panel A, Column 5)*	5.2	***1.6***	**8.8**	**9.2**	**15.2**	**8.4**
Piecewise linear with *NCO (Table 2, Panel B, Column 5)*	4.8	4.0	7.6	4.4	5.2	**11.6**
2000 random bank-quarters following Collins et al. (2017)						
Linear without *NCO (Table 2, Panel A, Column 4)*	6.4	***0.0***	**77.6**	**68.4**	**77.6**	***0.0***
Piecewise linear without *NCO (Table 2, Panel B, Column 4)*	6.4	6.4	6.4	2.0	2.8	8.4
linear with *NCO (Table 2, Panel A, Column 5)*	6.4	***0.8***	**9.6**	4.0	**14.0**	2.4
Piecewise linear with *NCO (Table 2, Panel B, Column 5)*	7.6	6.8	6.8	***0.4***	6.0	8.0

This table presents the rejection rates for the null hypothesis of no earnings management through discretionary loan loss provisions for 100 (2000) suspect earnings management banks against the alternative hypothesis of positive discretionary loan loss provisions (Panel A and B) or negative discretionary loan loss provisions (Panels C and D). In Panels A and C, 100 bank-quarters are randomly drawn from either the aggregate sample or each of the five quintiles of bank-quarters ranked by nonperforming loan change. We follow the test procedure of Kothari et al. (2005) and report the percentage of 250 simulation tests for which the null hypothesis of no earnings management is rejected at the 5% level using a one-tailed t-test. In Panels B and D, 2,000 bank-quarters are randomly drawn, 50% of which are from the quintile of bank-quarters ranked by nonperforming loan change of interest, and the other 50% of which are from the remaining four quintiles. We follow the test procedure of Collins et al. (2017) and report the percentage of 250 simulations tests for which the null hypothesis of no earnings management is rejected at the 5% level using a one-tailed t-test for mean. Rejection rates that are significantly less than the nominal significance level is in bold italics, and rejection rates that are significantly more than the nominal significance level is in bold.

TABLE 8

Power of Tests for Earnings Management through LLP (Type II Error)

Panel A: H1: Discretionary *LLP*>0

	All banks	*ΔNPL Bottom*	*ΔNPL Q2*	*ΔNPL Q3*	*ΔNPL Q4*	*ΔNPL Top*
Induced positive discretionary LLP						
Linear without *NCO (Table 2, Panel A, Column 4)*						
+1 bps	6.4	70.4	0.0	0.0	0.4	35.2
+3 bps	28.8	92.8	4.8	4.8	2.4	64.0
+5 bps	78.4	99.6	52.0	50.8	37.6	88.0
Piecewise linear without *NCO (Table 2, Panel B, Column 4)*						
+1 bps	7.2	5.6	13.2	17.2	14.0	5.2
+3 bps	31.2	22.4	81.6	87.6	82.0	16.4
+5 bps	81.6	58.4	99.2	100.0	100.0	42.0
linear with *NCO (Table 2, Panel A, Column 5)*						
+1 bps	12.8	24.4	24.8	24.8	14.8	10.8
+3 bps	68.6	62.8	92.4	97.2	91.2	43.6
+5 bps	98.4	92.8	100.0	100.0	100.0	81.6
Piecewise linear with *NCO (Table 2, Panel B, Column 5)*						
+1 bps	13.6	16.4	29.6	40.4	33.6	7.2
+3 bps	67.2	49.2	93.2	99.6	96.4	36.8
+5 bps	98.4	89.6	100.0	100.0	100.0	70.0

Panel B: H1: Discretionary *LLP*<0

	All firm	*ΔNPL Bottom*	*ΔNPL Q2*	*ΔNPL Q3*	*ΔNPL Q4*	*ΔNPL Top*
Induced negative discretionary LLP						
Linear without *NCO (Table 2, Panel A, Column 4)*						
-1 bps	19.6	0.4	80.0	72.4	81.6	2.0
-3 bps	48.8	2.0	96.8	92.8	96.0	8.0
-5 bps	72.8	8.4	99.2	98.4	98.4	19.2
Piecewise linear without *NCO (Table 2, Panel B, Column 4)*						
-1 bps	19.2	16.8	34.0	27.6	20.4	17.2
-3 bps	50.4	36.4	73.2	63.6	62.8	34.4
-5 bps	76.8	61.2	94.4	88.4	90.8	57.2
linear with *NCO (Table 2, Panel A, Column 5)*						
-1 bps	24.0	6.0	45.2	46.4	56.4	16.8
-3 bps	73.2	33.6	94.8	93.6	95.6	44.0
-5 bps	94.8	75.6	99.6	99.6	99.6	75.2
Piecewise linear with *NCO (Table 2, Panel B, Column 5)*						
-1 bps	24.0	14.0	41.2	28.8	32.4	22.0
-3 bps	74.8	50.8	92.0	91.2	90.0	50.8
-5 bps	94.8	84.4	99.6	99.6	99.2	78.4

This table reports the detection rates of earnings management through loan loss provisions from 250 tests where the null hypothesis of zero discretionary loan loss provisions is rejected against positive discretionary loan loss provisions (Panel A) or negative discretionary loan loss provisions at the 5% significance level using one-tailed t-test. In panel A (B), discretionary loan loss provisions equal to 1 (-1), 3 (-3), and 5 (-5) bps of loans are seeded into 100 randomly selected bank-quarters from either the aggregate sample (column 1) or each of the five quintiles of bank-quarters ranked by nonperforming loan change (columns 2-5).

TABLE 9

Replicating Liu and Ryan (2006) Table 2

	LLP			
	(1)	(2)	(3)	(4)
HIGHROA	-0.008***	-0.006***	-0.001	-0.001
	(-7.94)	(-6.22)	(-1.53)	(-1.40)
HOM%	-0.010***	-0.007***	-0.001	-0.001
	(-4.73)	(-3.70)	(-1.03)	(-1.00)
X	-0.006	0.032	0.102***	0.102***
	(-0.10)	(0.57)	(3.42)	(3.42)
*X*HIGHROA*	0.154***	0.103**	-0.017	-0.018
	(3.44)	(2.38)	(-0.74)	(-0.77)
*X*HOM%*	0.191**	0.172**	-0.024	-0.022
	(2.38)	(2.20)	(-0.58)	(-0.53)
CAP	-0.000***	-0.000***	-0.000***	-0.000***
	(-7.55)	(-7.82)	(-3.30)	(-3.48)
ΔNPL	0.058**	0.322***	0.135***	0.164***
	(2.20)	(5.99)	(8.30)	(5.09)
NCO			0.884***	0.880***
			(26.80)	(27.52)
DΔNPL		0.000		0.000***
		(0.45)		(2.84)
*DΔNPL*ΔNPL*		-0.483***		-0.027
		(-7.62)		(-0.72)
Fixed effects	Year	Year	Year	Year
N	3183	3183	3183	3183
adj. R^2	0.322	0.378	0.775	0.775

This table examines the effect of alternative loan loss provisioning models on Liu and Ryan's (2006) finding with respect to banks' earnings smoothing during the 1990 economic booms. Column (1) replicates their main finding using bank-year observations at the intersection of Bank Compustat Annual database and FR Y-9C bank holding company reports. Columns (2) - (4) add asymmetric nonlinearity, concurrent net loan charge-offs (NCO), and both asymmetric nonlinearity and concurrent net loan charge-offs respectively. Following Liu and Ryan, we adjust standard errors using White heteroscedasticity-consistent estimator.